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Bacterial Foraging Optimization Based Radial Basis Function Neural Network (BRBFNN) for Identification and Classification of Plant Leaf Diseases: An Automatic Approach Towards Plant Pathology

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ABSTRACT The contribution of a plant is highly important for both human life and environment. Plants do suffer from diseases, like human beings and animals. There is the number of plant diseases that occur and affects the normal growth of a plant. These diseases affect complete plant including leaf, stem, fruit, root, and flower. Most of the time when the disease of a plant has not been taken care of, the plant dies or may cause leaves drop, flowers, and fruits drop. Appropriate diagnosis of such diseases is required for accurate identification and treatment of plant diseases. Plant pathology is the study of plant diseases, their causes, procedures for controlling and managing them. But, the existing method encompasses human involvement for classification and identification of diseases. This procedure is time-consuming and costly. Automatic segmentation of diseases from plant leaf images using soft computing approach can be reasonably useful than the existing one. In this paper, we have introduced a method named as bacterial foraging optimization based radial basis function neural network (BRBFNN) for identification and classification of plant leaf diseases automatically. For assigning optimal weight to radial basis function neural network we use bacterial foraging optimization that further increases the speed and accuracy of the network to identify and classify the regions infected of different diseases on the plant leafs. The region growing algorithm increases the efficiency of the network by searching and grouping of seed points having common attributes for feature extraction process. We worked on fungal diseases like common rust, cedar apple rust, late blight, leaf curl, leaf spot, and early blight. The proposed method attains higher accuracy in identification and classification of diseases.

INDEX TERMS Bacteria foraging algorithm, image segmentation, plant diseases, radial basis function neural network, soft computing.

I. INTRODUCTION

Computers have evolved to be a vital device in a number of applications like defense, medical, agriculture, engineering etc. with its ability to process multimedia information like images captured from some computing devices. An image contains important information that can be retrieved by using some computational method. Image segmentation is a task for partitioning an image into smaller parts that are more meaningful. Interestingly, it can be stated as identification and classification of some region of interest. The segmentation is performed based on some common properties of the objects present in an image like color, texture and, shape etc. Image segmentation is a preprocessing step for image processing generally performed by using two methods (i) Traditional method and (ii) Soft computing method. The taxonomy of traditional method mainly compromises of thresholding, edge-based, region based, and clustering methods and soft computing mainly compromise of fuzzy logic, neural network, and genetic algorithm.

Soft computing having the capability to deal with uncertainty has been most widely used for image segmentation nowadays. Soft computing methods are designed to simulate human intelligence by learning from their skills to perform some complex task automatically. The Soft Computing (SC) methods is a group of methods mainly Fuzzy Logic (FL), Neural Network (NN), and Genetic Algorithm (GA) and Swarm Intelligence methods like Particle swarm optimization (PSO), Bacterial foraging optimization (BFO) etc. Soft computing methods generally do not require human intervention they perform the segmentation task automatically.

Plants play an important role in all the aspects of life. They serve as a backbone to sustain the environment. Plants do suffer from diseases, which affects the normal growth of plants. These diseases affect complete plant including leaf, flower, fruit and stem. Detection of such plant diseases is an important task to perform. The existing method for the identification and classification of diseases from a plant is done with the help of human intervention. Experts through naked eye make observations about the diseases of a plant by continuous monitoring of plants over a large period of time. Most of the time, these existing approaches of disease identifications are time-consuming and cumbersome. So to monitor the plant disease at an early stage, use of some automatic method can be quite beneficial. Soft computing technique having the ability to simulate human thinking is having the capability to perform the task of identification and classification of such plant diseases automatically in less time and cost.

In this article, we have presented an automatic soft computing approach BRBFNN for identification and classification of disease from plant leaves. The proposed method uses Bacterial Foraging Optimization (BFO) to assign optimal weight to Radial Basis Function Neural Network (RBFNN) and to find the optimal region for the different disease present on the plant leaves. RBFNN is the special linear function having a unique competence of which increases or decreases monotonically with distance from the center point capable of handling the complexity of the affected region exists on the plant leaf images. The efficiency of the Radial Basis Function neural network is further enhanced for region growing method used seed points and grouping them having similar attributes that help in feature extraction process. BFO with its mimicking capability and multi-optimal function verifies to be an efficient and powerful tool for initializing the weight of RBFNN and training the network that can correctly identify different regions on plant leaf image with high convergence speed and accuracy.

The identification and classification of plant diseases using some automatic intelligence approach can have the expected significance such as

1) Farmer's cognizance regarding the fertilizers to be adopted and metric formation using some parameters related to a product such as a durability, cost, future needs and quality assurance etc.

2) Predetermination of the plant utilization based on the perilous climatic conditions that deleterious the plantation.

The organization of the paper is as follows section II gives the related work, section III presents the methodology of the proposed algorithm for image segmentation, section IV introduces various plant diseases, section V gives the proposed method for identification and classification of diseases, section VI offer the outcomes of the proposed approach and section VII concludes the article with future work followed by references.

II. RELATED WORK

Identification and classification of plant leaf disease is a complicated task to perform. Many researchers have worked on both traditional and soft computing approached for the segmentation of infected area of leaves from the disease. In this part, we try to encapsulate some of the soft computing approaches that have been utilized to perform this task. Support vector machine with radial basis function being its kernel has been used most often to identify and classify the disease present with an image of leaf with the disease. The neural network with its learning and training capabilities has also been deployed for this task. Table 1 shows the number of soft computing methods that have been used to identify the disease of the plant.

Generally, it has been seen from the literature that SVM has been applied for the identification of plant diseases. Whereas the learning ability of NN also contributes for the same purpose. As it is seen from the survey authors have majorly focused on the identification of a disease from the specific plant because it is a hard task to identify and categorize the disease among different categories. As deep learning algorithms are appearing in the number of applications a novel work introduced by Yang Lu et al. have applied convolutional neural network for the identification of rice diseases. Shanwen Zhang et al. uses K-means clustering for the identification of cucumber leaf diseases. There are number of applications using SVM have been presented like Pranjali B. Padol et al. uses it for identification of grapes leaf disease, Jagadeesh D. Pujari et al. for identification of plant leaf disease of crops such as wheat, maize, grape and sunflower etc., Sushma S. Patil et al. for identification of tomato leaf disease, Marion Neumann et al. for beet leaf disease, Rong Zhou et al. for identification of Cercospora leaf Spot form sugar beet and so on. Though the researchers have worked with SVM, the problem of identifying multiple diseases by using SVM will be a complicated task, because of this the efficiency of the system will decrease both in the terms of cost and time. In this paper, we have introduced radial basis function network have been trained with bacterial foraging algorithm that is robust in nature for abrupt changes occur in leaf diseases and network along with radial basis function for feature extraction to identify and classify six fungal plant leaf diseases correctly.

III. METHODOLOGY

In this work identification and classification of plant leaf disease is performed by using Bacterial foraging optimization based Radial Basis Function Neural Network (BRBFNN). The feature extraction process is carried out by seeding and

TABLE 1. Review for segmentation of plant leaf disease using soft computing methods.

Year	Author	Method	Application area
2017	Shanwen Zhang et al.	K-means clustering	Identification of cucumber leaf diseases
2017	Yang Lu et al.	Convolutional neural network	Identification of rice diseases
2017	Tallha Akram et al.	Based on an Image processing technique	Real time classification of plant diseases
2017	Trimi Neha Tete et al.	Neural network, K-means and thresholding	Identification of disease from potato, apple and mango leaves
2017	Vijai Singh et al.	Genetic algorithm	Identification of diseases from rose, beans, lemon, and banana plant leaves
2017	Megha. S et al.	Fuzzy c means and Support vector machine	Identification of plant leaf disease
2017	Lin Yuan et al.	Fisher's linear discriminant analysis (FLDA)	Identification of plant diseases and pests from SAR images
2016	Pranjali B. Padol et al.	Support vector machine	Identification of grape leaf disease
2016	Jayme Garcia Arnal Barbedo et al.	Based on an Image processing technique	Identification of leaf disease from 12 different species of plants
2016	Jayamala Kumar Patil et al.	Content based image retrieval	Identification of soybean leaf diseases
2016	Jagadeesh D. Pujari et al.	Support vector machine and artificial neural network	Identification of plant leaf disease of crops such as wheat, maize, grape, sunflower etc.
2016	Iqbaldeep Kaur et al.	Support vector machine and Ant colony algorithm	Identification of plant leaf
2015	Ramakrishnan. M et al.	Backpropagation algorithm	Identification of groundnut leaf disease
2016	Malvika Ranjan et al.	Artificial neural network	Identification of cotton leaf disease
2015	Santanu Phadikar et al.	Genetic algorithm and rough set theory	Identification of rice leaf disease
2015	Prakash M. Mainkar et al.	K-means clustering, Gray level Co-occurrence matrix and Backpropagation neural network	Identification of disease from potato, tomato and cotton leaves
2014	Sushma S. Patil et al.	Support vector machine	Identification of tomato leaf disease
2014	Marion Neumann et al.	Support vector machine	Identification of beet leaf disease
2014	K. P. Waidyarathne et al.	Self-organizing map and multilayer perceptron	Identification of Weligama coconut leaf wilt disease (WCLWD)
2014	Lin Yuan et al.	Fisher linear discrimination analysis (FLDA) and Partial least square regression (PLSR)	Identification of wheat leaf diseases
2014	Rong Zhou et al.	Support vector machine	Identification of Cercospora Leaf Spot form Sugar beet
2010	T. Rumpf et al.	Support vector machine	Identification of Sugar beet disease from leaves
2010	Zhan-Yu Liu et al.	Learning vector quantization neural network and principal component analysis	Classification and identification of fungal infection levels from rice panicles
2009	A. Camargo et al.	Support vector machine	Identification of plant leaf disease

grouping the points having similarity in some manner using region growing approach the training of the RBFNN is performed by using bacterial foraging optimization that proofs to be an efficient and powerful tool for initializing the weight of RBFNN and training the network that can correctly identify different affected regions on plant leaf image. With the help of BFO, the proposed algorithm achieves higher convergence ratio and accuracy. The methodology of the proposed work is given by Fig. 1.

IV. PLANT DISEASES

Plants do suffer from diseases, like human beings and animals. These diseases affect a complete plant including leaf, stem, fruit, root and flower. There is the number of plants diseases that occur and affects the normal growth of a plant. Most of the time when the disease of a plant has not been taken care of, the plant dies or may cause leaves drop, flowers and fruits drop etc. Appropriate diagnosis of such diseases is required to for accurate identification and treatment of plant diseases. The diagnosis of diseases depends upon aspects like

1) Looking for signs or symptoms: can be seen by naked eyes are the appearance of some unwanted spots, dead areas etc. on the part of the plant.

2) Having the knowledge of the normal characteristics of the host plant: one should know about the properties of the host plant then it is easier for one to diagnosis the plant disease.

3) The timing of symptoms: it depends upon two factors 1. Disorder and 2. Diseases. Disorders are caused based on some environmental problems, happens suddenly like within a day or week and does not spread over the parts of the plant. Whereas, diseases are slow takes several days, weeks, months or even a year to grow, having the property of affecting the other parts of the plant.

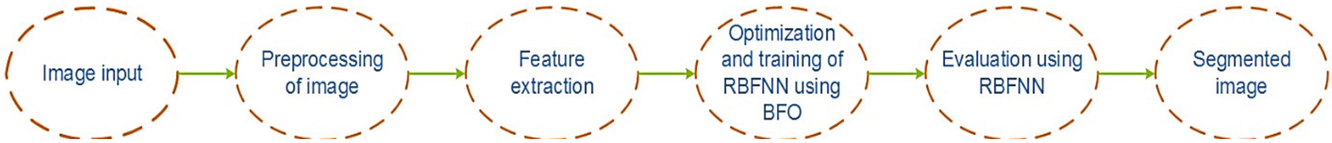


FIGURE 1. Methodology for the proposed work.

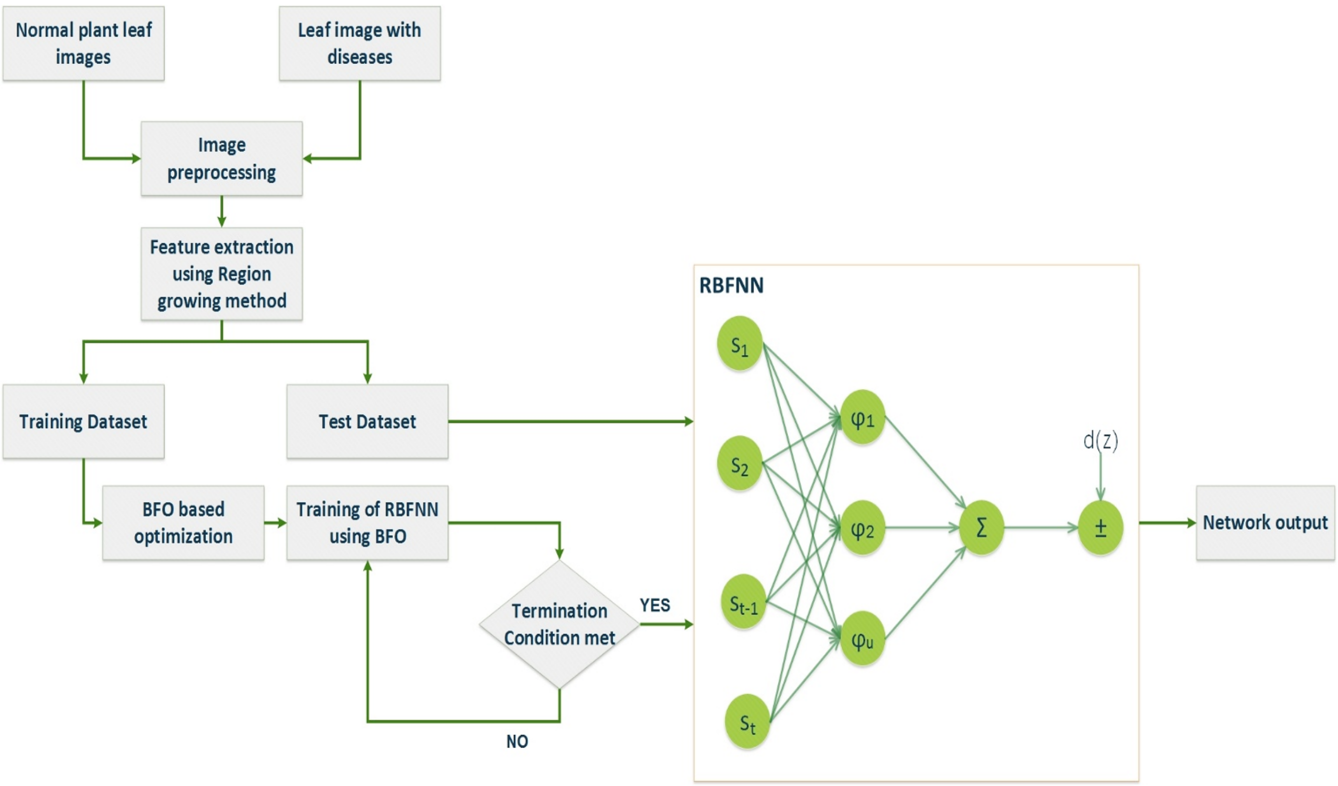


FIGURE 2. Flowchart for our proposed work.

4) Noticing the pattern of the diseases on the host plant: patterns can be uniform and non-uniform in nature. Uniform is known as abiotic that are caused by non-living factors and non-uniform are biotic that are caused by some disease or insect.

The plant diseases are generally classified into three categories 1. Bacteria 2. Fungus and 3. Virus. In this article, we have focused upon fungal diseases identification that affects the plant on a large scale. Fungi is the disease that attains their energy from the plant they live upon. Fungi disease is responsible for a significant amount of damage. According to a study, about 85% of all plant diseases are caused by fungi. The fungi diseases that were considered in this work for identification and classification are given in Table 2.

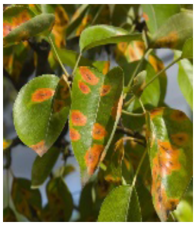
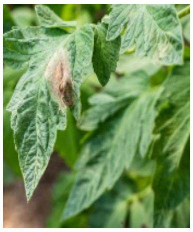
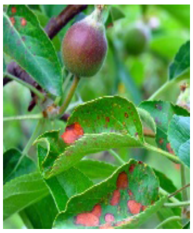
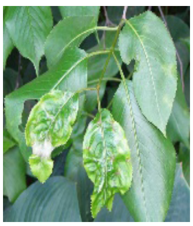
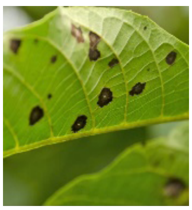
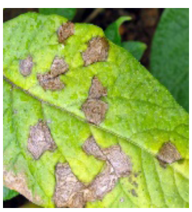
V. PROPOSED WORK

In our proposed work, we focus on identification and classification of plant diseases using some computational intelligence approach. The proposed method uses Radial Basis Function Neural Network (RBFNN) that is trained with the help of Bacterial Foraging Optimization (BFO), to find the affected region via different diseases present on plant leaves. RBFNN is the special linear function having a unique competence of which increases or decreases monotonically with distance from the center point capable of handling the complexity of the affected region exists on the plant leaf images. The efficiency of the Radial Basis Function Neural Network is further enhanced by using region growing method searching for seed points and grouping them having similar attributes that help in feature extraction process. BFO with its mimicking capability and multi-optimal function verifies to be an efficient and powerful tool for initializing the weight of RBFNN and training the network that can correctly identify different regions on plant leaf image with high convergence speed and accuracy. A flowchart of our proposed work is given in Fig. 2.

A. REGION GROWING ALGORITHM (RGA) FOR FEATURE EXTRACTION

RGA is a simple approach that starts with the set of seed points and grows by using these seed points forming a

TABLE 2. Fungal plant diseases classification.

Leaf Image	Disease name	Cause / Symptoms	Effect	Suitable Climatic conditions
	Common rust (*Phragmidium* spp.)	Puccinia sorghi / White, slightly raised spots on the undersides of leaves and on the stems. After sometime, these spots become covered with reddish-orange spore masses. Later, leaf pustules may turn yellow-green and eventually black	Most commonly found on corn leafs causes leaf drop	Cool temperature
	Late Blight	*Phytophthora infestans* / Late blight first appears on the lower, older leaves as water-soaked, gray-green spots	Leaf, fruits and stems get of tomato and potato plants are effected Leaf spots darken and a white fungal growth forms on the undersides. Eventually the entire plant will become infected. Crops can be severely damaged	Wet, humid conditions
	Cedar apple rust	*Gymnosporangium juniperi-virginianae* / Generally appears to be bright orange-yellow spots	Primarily effects apples and crabapples. The leaves that are heavily infected leaves may drop prematurely	Wet weather (Early Spring season)
	Leaf curl	*Taphrina deformans* / Reddish areas on developing leaves. These areas become thick and puckered causing leaves to curl and distort	Observed on peaches, almonds, apricots and nectarines plants. Severe, leaf curl can substantially reduce fruit production	Cool wet weather (Spring season)
	Leaf spot	Parasitic fungi / Infected plants have brown or black water-soaked spots on the foliage, sometimes with a yellow halo, usually uniform in size	Found on an ornamental or shades trees. As spots become more numerous, entire leaves may yellow, wither and drop	Moisture and warm temperatures
	Early blight	*Alternaria solani* and *Alternaria tomatophila* / On the lower, older leaves as small brown spots with concentric rings that form a "bull's eye" pattern	Leaf, fruits and stems get of tomato and potato plants are affected. Leaf surface causing it to turn yellow, wither and die	Wet, humid conditions

region by appending to each seed the adjoining pixels, having analogous features to the seed such as intensity level, color, or scalar properties for the grayscale images. RGA method delivers the benefit of choosing several measures for selecting a seed point. There are two basic schemes for this technique termed as 4-neighborhood and 8-neighborhood. The 4-neighborhood leaving diagonally associated regions selects adjacent regions while 8-neighborhood selects both diagonal regions and adjacent regions while growing procedure.

Rules for region growing are as follows:

1) $\bigcup_{i=1}^{n} R_i = R$
2) R_i is a connected region $i = 1, 2, \ldots n$
3) $R_i \cap R_j = \emptyset$ for all $i = 1, 2, \ldots n$

4) $P(R_i) = \text{TRUE}$ for $i = 1, 2, \ldots n$
5) $P(R_i \cup R_j) = \text{FALSE}$ for any adjacent region R_i and R_j where $P(R_i) =$ logical predicate defined over the points in set R_i and $\emptyset =$ null set.

B. BACTERIAL FORAGING OPTIMIZATION (BFO) FOR TRAINING THE NETWORK

BFO is new nature-inspired optimization algorithm proposed by Kevin Passino in 2002. The group foraging behavior of bacteria such as M. Xanthus and E. Coli. motivated the development of BFO. BFO algorithm is inspired by the chemotaxis behavior of virtual bacteria that move towards (in the direction of) or away (not in the direction of) from the specific signals taking small steps while searching for nutrients in the problem search space is another key concept for BFO. BFO has turned out to be an effective and influential optimization tool that provides high convergence speed and accuracy applied in the number of the real world applications. The proposed method has been trained by using the four basic steps of BFO are given below:

1) CHEMOTAXIS

Chemotaxis is the process of movement of E. Coli that searches nutrient-rich location via flagella (locomotory organelles). When the searching is in the same direction of the preceding step than this process is known to be swimming and when the searching is in opposite direction from the preceding step than this process is known to be tumbling. The chemotactic movement of the bacterium is defined by Refer to (1).

$$\varphi^i(x+1, y, z) = \varphi^i(x, y, z) + C(s)\frac{\Delta(s)}{\sqrt{\Delta^T(s).\Delta(s)}} \quad (1)$$

where $\varphi^s(x, y, z) = s$ bacterium at x^{th} chemotactic, $y =$ reproductive, $z =$ elimination-dispersal step, $C(s) =$ size of the unit step taken in the random direction, $\Delta(s) =$ indicates a vector in the arbitrary direction whose elements lies in $[-1, 1]$.

2) SWARMING

Bacteria like E. Coli and S. Typhimurium, when stimulated by a high level of succinate, shows an interesting group behavior by releasing an attractant aspartate. These aspartates assistance the nutrient gradient having the specific pattern in moving up of the swarm with high velocity. Using attractant and repellent the cell to cell communication for swarm is Refer to (2).

$$\begin{aligned} &J_{cc}(\varphi(s, x, y, z)) \\ &= \sum_{s=1}^{S} J_{cc}\left(\varphi, \varphi^s(x, y, z)\right) \\ &= \sum_{s=1}^{S}\left[-b_{attractant}\exp\left(-c_{attractant}\sum_{m=1}^{p}(\varphi_m - \varphi_m^s)^2\right)\right] \\ &\quad + \sum_{s=1}^{S}\left[d_{repellant}\exp\left(-c_{repellant}\sum_{m=1}^{p}(\varphi_m - \varphi_m^s)^2\right)\right] \end{aligned} \quad (2)$$

where $J_{cc}(\varphi(s, x, y, z))$ is an objective function, S is the total number of bacteria population, p is no. of variables to be optimized, $\varphi = [\varphi_1, \varphi_2, \ldots, \varphi_p]^T$ is point in the p-dimensional search domain, $b_{attractant}$, $c_{attractant}$, $d_{repellant}$, and $c_{repellant}$ are measure of quantity and diffusion rate of the attractant signal and the repellent effect magnitude.

3) REPRODUCTION

For maintaining the population to be constant reproduction is the process in which the unhealthy bacteria are dies and the healthy bacteria crossover asexually split into two bacteria having the same direction. After traveling N_c chemotactic steps the fitness value of the s^{th} bacteria is Refer to (3)

$$J_{health}^s = \sum_{x=1}^{N_c+1} J^i(x, y, z) \quad (3)$$

where J_{health}^s represents the health of sth bacterium.

4) DISPERSAL AND ELIMINATION

There is the number of reason that could affect the native surroundings and may cause fluctuations in the bacterium population where they exist. The rise in temperature causes a high concentration of nutrient gradients or events due to which all the bacteria in a region are killed or moved to another region. The new replacements are randomly initialized over the search space to handle such situation with some bacteria are liquidated at random with a very small probability.

C. RADIAL BASIS FUNCTION NEURAL NETWORK (RBFNN)

RBFNN consists of three layers namely (i) input layer, (ii) hidden layer, and (iii) output layer. The network is are the feed-forward network. The functionalities of the input layer are the same as for other networks i.e. for taking input and providing output, the major difference for any network is lies within the working of hidden layer. In this network the hidden layer contains the specific activation functions known as Radial Basis Function (RBF). Other than that the hidden layer also comprises of radial kernel functions and output layer comprises of linear neurons. The network compromises of neurons with ''local'' or ''tuned'' receptive fields that can be biologically motivated with somatosensory cells reactive to precise body regions or orientation-selective cells in visual cortex. RBF termed as to be a special class of linear function having a unique feature, of which response decreases or increases monotonically with distance from a center point. The hidden layer is responsible for carrying out non-linear transformation of input and output layer performing linear regression to envision the anticipated outputs. RBF is different from the other networks having multiple hidden layers active at a time. Although there are many radial kernels available to be used for RBF, the Gaussian and Multiquadric are frequently used. A Gaussian RBF having the property of monotonically decreasing with the distance from the center and Multiquadric RBF having the property of monotonically increasing with the distance from the center. The scalar input for Gaussian and Multiquadric are Refer to (4) and (5)

$$Gaussian\ \phi = exp\left(-\frac{(\gamma - u)^2}{v}\right) \tag{4}$$

$$Multiquadric\ \phi = \frac{\sqrt{v^2 + (x-u)^2}}{v} \tag{5}$$

where u = centre and v = radius

The proposed k dimensional input vector γ is fed to each of the i^{th} radial basis hidden units. The hidden layer is a radial center denoted by $u_1, u_2, \ldots, u^h$ for every unit. The output of the i^{th} hidden unit will be Refer to (6)

$$\phi_i = \phi(||\gamma - c_j||) = exp\left(-\frac{||\gamma - u_i||^2}{2\sigma_i^2}\right) \tag{6}$$

where the input vector $\gamma' = \{s_1, s_2, \ldots, s_t\}$, $||\ ||$ is the Euclidean distance between the input and the i^{th} center, $\varphi(.)$ is the RBF function and δ_i is the standard deviation of the i^{th} Gaussian function, Refer to (7)

$$\delta = d_{max}/\sqrt{h} \tag{7}$$

where d_{max} is the maximum distance between the centers and the output y of the network is Refer to (8)

$$y = \sum\nolimits_{i=1}^{n} w_i \cdot \phi(||\gamma - u_i||) \tag{8}$$

where w_i is the weight of the i^{th} hidden unit and h is the number of centers. The weight of RBF will be obtained by network training using metaheuristic approach BFO.

VI. RESULTS

The proposed work was implemented on MATLAB 2016b working on a system with an i3 processor having 4GB RAM. For validating the effectiveness of this work we have taken two sets of images. The first set consisted of 6 different images with 6 different diseases is selected from planet natural and second dataset consists of about 270 images are selected from crowdAI.org (PlantVillage Disease Classification Challenge) categorizing among the same 6 set of diseases. The result part is divided into two categories (A) To correctly segment/identify the infected area on plant leaf for a disease and (B) To classify the type of leaf disease. The performance evaluation of the proposed work for correctly identifying the affected area or disease on the plant leaf is evaluated using two quantitative evaluation parameters that are based on the statistical performance of the ground truth image and segmented image. The parameters are specificity and sensitivity Refer to (9) and (10). The most critical part is the classification of diseases based on some attributes associated with them. The performance of the proposed work for correctly classifying diseases is done by using two entropy functions known as Validation evaluation partition coefficient V_{pc} and Validation evaluation partition entropy V_{pe} Refer to (11) and (12).

$$Specificity = \frac{TN}{TN + FP} \tag{9}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{10}$$

where True Positive (TP) = no. of pixels exactly classified, False Positive (FP) = no. of pixels incorrectly classified, True Negative (TN) = no. of pixels exactly misclassified, and False Negative (FN) = no. of pixels incorrectly misclassified. The value of specificity and sensitivity lies between 0 and 1 when result is equal to 1 means perfect segmentation.

$$V_{pc} = \sum\nolimits_{k=1}^{K} \sum\nolimits_{i=1}^{N} \frac{u_{ik}^2}{N} \tag{11}$$

$$V_{pe} = -\sum\nolimits_{k=1}^{K} \sum\nolimits_{i=1}^{N} \frac{u_{ik}\log(u_{ik})}{N} \tag{12}$$

where u_{ik} is the membership value of pixel i belonging to the k-th cluster, K is the number of clusters and N is the total number of image pixels. Both functions value lies between 0 and 1, when V_{pc} is high and V_{pe} is low, it implies the membership values are less in segmentation results and the tissues are classified correctly.

A. SEGMENTATION OR IDENTIFICATION OF PLANT LEAF DISEASES

The symptoms of the occurrence of diseases on plant leafs vary depending on the number of features. Segmentation of the disease region accurately is a complicated task to perform. Features like shape, color, and size etc. of the disease differ for diverse diseases. The region growing method is used searching for seed points and grouping them having similar attributes that help in feature extraction process. The original image has been processed and converted to a segmented grayscale image. The mask creation of the grayscale image has been done to improve the results finally obtaining the affected region on a plant leaf affected by some disease. The results of the segmentation using BRBFNN have been given in Fig. 3. The evaluation of the proposed work is done based on two quantitative evaluation parameters known as specificity and sensitivity. For validating the segmentation performance of BRBFNN two other algorithms K-means (KM) and Genetic Algorithm has been considered. The average specificity value with 0.8558 for the proposed work shows higher accuracy for identification of diseases when applied on six different images with six different diseases compared to that of 0.7914 for KM and 0.8139 for GA. The highest segmentation accuracy with specificity value 0.8897 is attained by the proposed algorithm for correctly identifying early blight. It is seen from the results that if the network is trained properly then the probability of finding the region of disease increases. As in the case of identification of leaf curl (a critical region to identify) with the specificity of about 0.8879 when compared to that of 0.7517 for KM and 0.7989 for GA. The comparative results based on specificity for KM, GA, and BRBFNN have been given in Table 3. Fig. 4 and Fig. 5 shows the comparative graphical analysis KM, GA, and BRBFNN for specificity and sensitivity.

The proposed method achieves the average sensitivity of 0.8705 that shows higher performance to the average

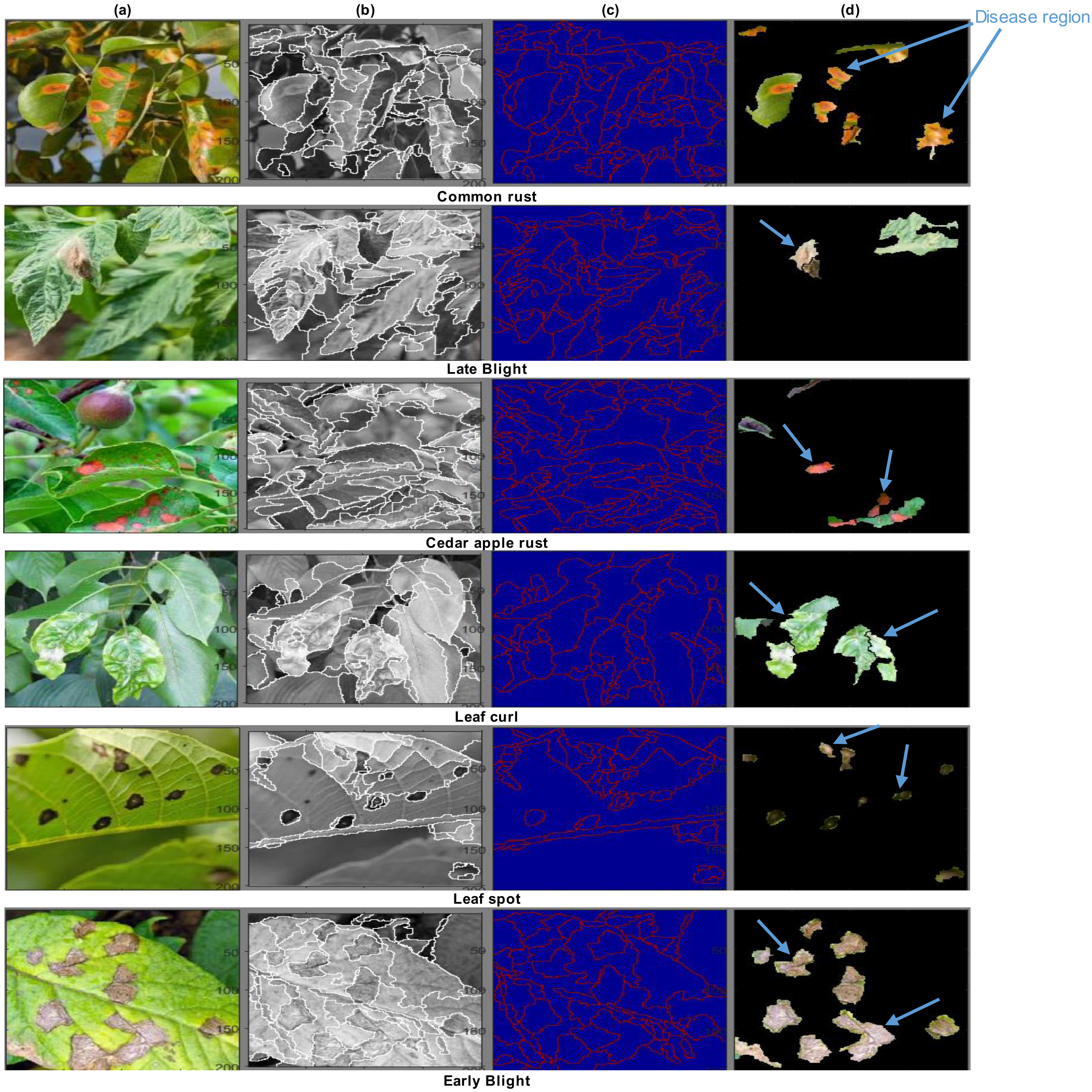


FIGURE 3. Results for BRBFNN (a) Original image (b) Segmented gray scale image (c) Creation of mask and (d) Segmented results for leaf disease.

sensitivity performance of 0.8020 for KM and 0.8244 for GA. In this case, the leaf curl disease has been significantly identified by our work with a sensitivity of about 0.8938 shows the effectiveness of the proposed work. The comparative results based on sensitivity for KM, GA and BRBFNN have been given in Table 4.

Further to verify the performance of the proposed work a dataset with 270 images is selected that has been classified with the same set of diseases. For evaluation purpose, the results of the proposed work are compared with the results of KM and GA methods respectively. The average specificity and sensitivity for the proposed work are found to be 0.8231 and 0.8357 shows the superiority of the algorithm when compared to the specificity and sensitivity of about 0.7596 and 0.7618 for KM and 0.7814 and 0.7968 for GA respectively. The computational efficiency for correctly identifying the diseases for the proposed algorithm is about 13.47s on average.

TABLE 3. Comparative results for identification of leaf disease based upon specificity for K-means, genetic algorithm, and proposed BRBFNN methods.

Disease	K-means (KM)	Genetic algorithm (GA)	BRBFNN
Common rusts	0.7817	0.8096	0.8213
Late Blight	0.8014	0.8205	0.8326
Cedar apple rust	0.7801	0.7854	0.8196
Leaf curl	0.7517	0.7989	0.8879
Leaf spot	0.8124	0.8318	0.8836
Early blight	0.8211	0.8374	0.8897
Average Specificity	0.7914	0.8139	0.8558

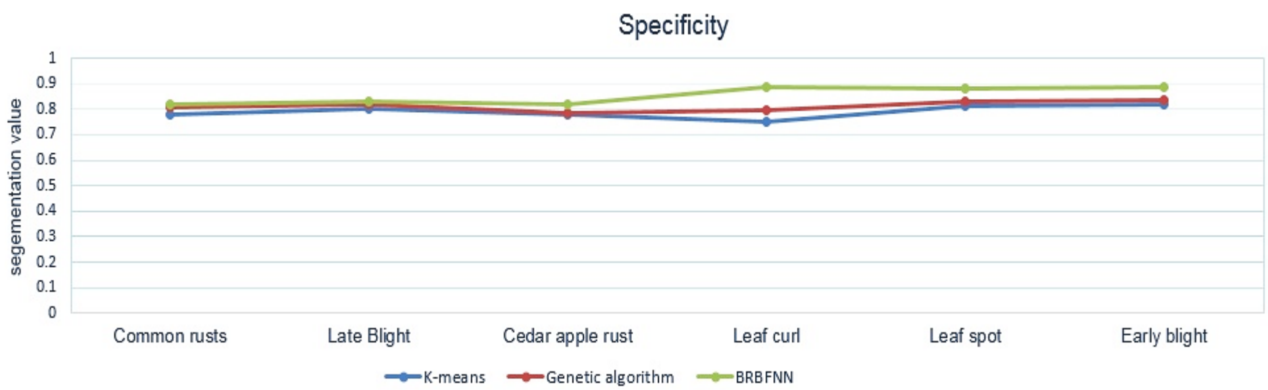


FIGURE 4. Comparative analysis for Specificity.

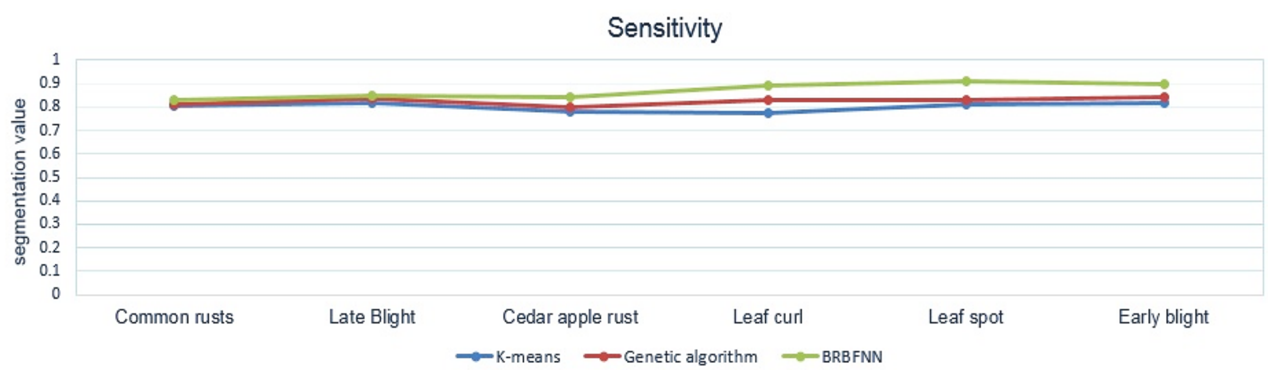


FIGURE 5. Comparative analysis for Sensitivity.

B. CLASSIFICATION OF PLANT LEAF DISEASES

The classification of a disease is another challenging task to obtain. This is due to the region of similarity of the characteristics of the number of plant diseases. The classification accuracy of the proposed method has been verified using V_{pc} and V_{pe}. Comparative analysis of the proposed method has been done with GA and SVM. Table 5 and Table 6 show the result for the classification accuracy. Proposed method achieved higher classification accuracy with $V_{pc} = 0.8621$ and $V_{pe} = 0.1118$ respectively when compared with that of 0.8113 and 0.1933 for GA and 0.8337 and 0.1665 for SVM respectively for the set of six different images with different diseases. Fig. 6 and Fig. 7 shows the graphical analysis for V_{pc} and V_{pe} values for GA, SVM, and BRBFNN. The proposed algorithm attains higher results for the other set of images with $V_{pc} = 0.8307$ and $V_{pe} = 0.1527$ respectively when compared with that of 0.7635 and 0.2240 for GA and 0.7853 and 0.1984 for SVM respectively. The computational efficiency for correctly classifying the diseases for the proposed algorithm is about 19.33s on average.

TABLE 4. Comparative results for identification of leaf disease based upon sensitivity for K-means, genetic algorithm, and proposed BRBFNN methods.

Disease	K-means (KM)	Genetic algorithm (GA)	BRBFNN
Common rusts	0.8078	0.8117	0.8311
Late Blight	0.8189	0.8339	0.8497
Cedar apple rust	0.7809	0.7996	0.8407
Leaf curl	0.7729	0.8279	0.8938
Leaf spot	0.8111	0.8315	0.9078
Early blight	0.8201	0.8417	0.8999
Average Sensitivity	0.8020	0.8244	0.8705

TABLE 5. Classification accuracy for GA, SVM and BRBFNN based on V_{pc}.

Disease	Common rusts	Late Blight	Cedar apple rust	Leaf curl	Leaf spot	Early blight	Average V_{pc}
GA	0.8124	0.8201	0.7987	0.7798	0.8214	0.8351	0.8113
SVM	0.8559	0.8489	0.8135	0.7935	0.8397	0.8504	0.8337
BRBFNN	0.8871	0.8697	0.8298	0.8298	0.8649	0.8914	0.8621

TABLE 6. Classification accuracy for GA, SVM and BRBFNN based on V_{pe}.

Disease	Common rusts	Late Blight	Cedar apple rust	Leaf curl	Leaf spot	Early blight	Average V_{pe}
GA	0.1935	0.1786	0.2314	0.2478	0.1587	0.1496	0.1933
SVM	0.1607	0.1485	0.2159	0.2087	0.1398	0.1255	0.1665
BRBFNN	0.1033	0.0978	0.1579	0.1429	0.0890	0.0801	0.1118

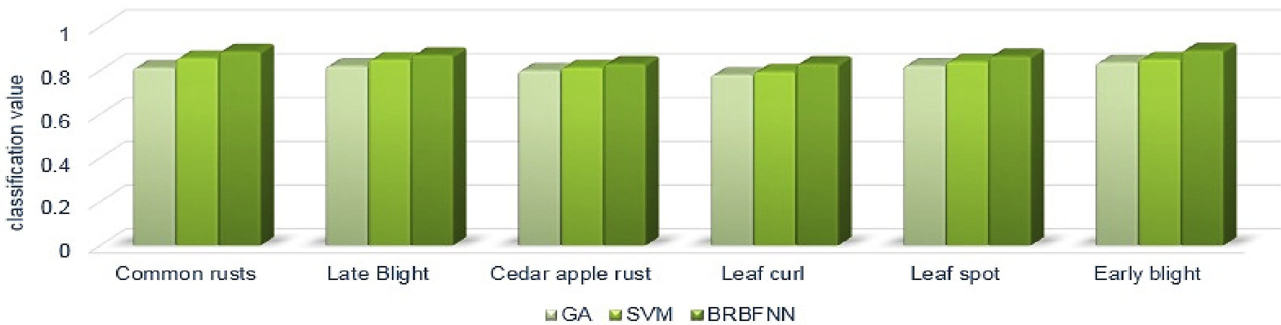


FIGURE 6. Comparative graph for V_{pc}.

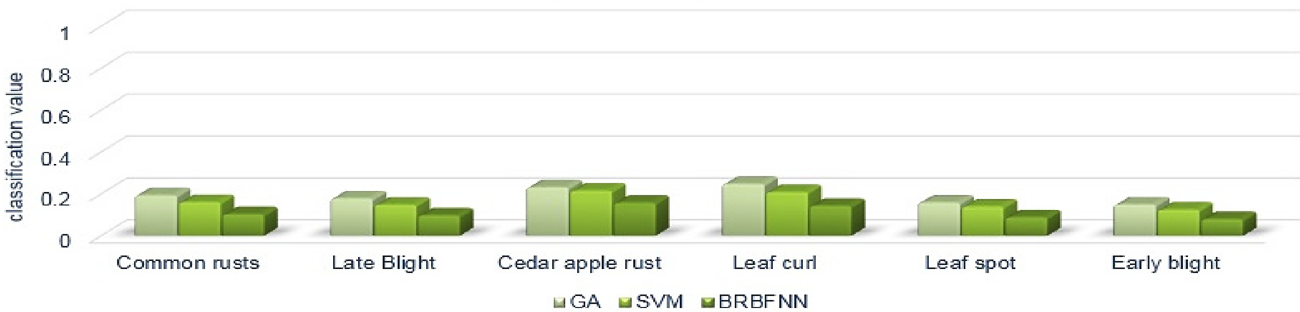


FIGURE 7. Comparative graph for V_{pe}.

VII. CONCLUSION

The plant serves as the basic need for any living organisms. They are the most important and integral part of our surroundings. Just like a human or other living organism does plant do suffer from different kind of diseases. Such diseases are harmful to plant in a number of ways like can affect the growth of the plant, flowers, fruits, and leaves etc. due to which a plant may even die. So in this work, we have proposed a novel method named as Bacterial foraging optimization based Radial Basis Function Neural Network (BRBFNN) for identification and classification of plant leaf diseases. The results, when compared with other methods, show that the proposed method achieves higher performance both in terms of identification and classification of plant leaf diseases. The segmentation result for BRBFNN based on specificity and sensitivity for the first set of images is found to be 0.8558 and 0.8705 and on the second set of images was 0.8231 and 0.8357 respectively. The classification results for BRBFNN based on V_{pc} and V_{pe} for the first set of images is found to be 0.8621 and 0.1118 and on the second set of images was $V_{pc} = 0.8307$ and $V_{pe} = 0.1527$ respectively. The proposed method is also superior in terms of computational efficiency for identification and classification of diseases. For this work, we have worked with only fungal diseases, in future, this work can be extended working on with different databases with dissimilar diseases like bacteria or viruses.

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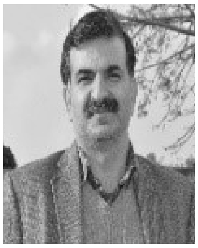

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